Evidence Report

Risk of Inadequate Design of Human and Automation/Robotic Integration

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Risk Title

The ***Risk of Inadequate Design of Human and Automation/Robotic Integration*** is identified by the NASA Human Research Program (HRP) as a recognized risk to human health and performance in space. The HRP Program Requirements Document (PRD) defines these risks. This Evidence Report provides a summary of the evidence that has been used to identify and characterize this risk.

Risk Statement

Given that automation and robotics must seamlessly integrate with crew, and given the greater dependence on automation and robotics in the context of long-duration spaceflight operations, there is a risk that systems will be inadequately designed, resulting in flight and ground crew errors and inefficiencies, failed mission and program objectives, and an increase in crew injuries.

Risk Overview

National Aeronautics and Space Administration (NASA) future missions will depend on humans interacting with automated and robotic systems to accomplish mission goals. This will be the case for both near- and deep-space exploration missions, including near-Earth object (NEO) and planetary surface operations. It will be the case for crew in space and controllers on the ground.

To carry out NASA's vision, operations involving crew-robot and crew-automation interactions will increase substantially relative to current operations. The systems required to support these operations will provide a highly diverse set of functions and will require diverse forms of control. The classes of robotic systems required for these missions will include dexterous, heavy-lift, and mobility systems. The required automation systems will span ground and flight systems and will support functions from controlling the habitat to conducting science experiments.

These mixed-initiative systems will have to support multiple operators, varying time delays, and increased reliance on high and variable levels of automation. Human-robot teaming will be a cornerstone of future operations. Hence, robotic systems and their human interfaces must be designed to support all levels of human operation (direct manual control, shared control, and supervisory control). They must also support multiple robot operators in multi-agent team configurations, with those operators separated by time, space, or both. Similarly, the integration of automation systems with their human users requires supporting a variety of role divisions: authority and autonomy can be differently allocated between human and automation, and that

allocation may change dynamically depending on task or context.

Ineffective user interfaces, poor system designs, or ill-advised functional task allocation compromise mission success and safety. There are gaps in our knowledge and experience for this level of complexity of automated or robotic operations. Concerning robotics, risk arises because we have limited experience with teleoperation, time-delayed operations, and multi-agent paradigms. For example, poorly designed human interfaces can result in a loss of situation awareness, compromising mission safety and efficiency. Of special concern are losses of situation awareness that occur while a crewmember is in close proximity to a robot, with the consequent risk to crew safety. Crew must be able to ascertain and understand the state of a robot, affect or change its command, and override the system whenever necessary.

Currently, most work in space is performed by the crew, supported to some degree by on-board automated systems (e.g., for environment control) and to a larger degree by ground-based Mission Control. As space missions' scope expand in distance and duration, and as the tasks executed in space become more complex, increased support by automation will be necessary. Proper human-automation integration will be critical in space as well as on the ground. In space, more tasks will need to be completed by fewer people, with fewer external resources and support. In addition, crewmemberss will have less training and experience in any particular activity compared to the corresponding member of a larger team with a specialist for that activity. Further, the role of ground control will change. Ground control will need to provide different forms of support for the crew and vehicle, focusing more on longer-term projections, modeling, anticipatory troubleshooting, and monitoring health of systems and crew.

In short, mission complexity will increase as mission familiarity and experience decrease. This means that the challenges to effective design of automation and robotics, and of the human-system integration, also increase. A critical aspect to meeting automation design challenges is a focus on integration (Terwiesch & Ganz, 2009). Automation/robotics must be well integrated into the process and the work flow it is designed to support. Further, complex missions require multiple automation systems and robots, as well as multiple people. Design with an awareness of how multiple "agents", be they people, automation, or robots, can and should coordinate and integrate their activities is critical as well. Automation is never a direct matter of taking one task from human responsibility and simply assigning the identical task to automation/robotics; automation changes the work, shifts times of peak human workload, and creates new, often challenging tasks for humans such as supervisory responsibility.

Many factors affect the adequacy of designs of human and automation/robotic integration, and an inadequate design can produce many interrelated effects. Effective intervention to minimize risk from inadequate design requires a multi-faceted, systems-level approach.

One potential cause of poor design is an inappropriate acquisition process. That is, insufficient attention may be given to requiring sound human and automation/robotic integration in procurement or there may be inadequate methods for ensuring delivery of sound design, even with intent to require it. There may be insufficient attention to identifying the expected functions of the automation/robotic system or of the unexpected functions that users might ask of it. Design of effective human automation/robotic interaction (HARI) also requires an analysis of the way that functions should be distributed among humans, robots, and automated systems, and should consider the extent to which particular function allocations between humans and automation or robots should be fixed or flexible. Additional factors where poor integration may be manifest include:

- inefficiency of interactions among operators (both ground and crew controllers), automation, and robotic agents;
- incompleteness or inconsistency of situation awareness by the crew and the ground controllers; and
- poor arbitration of command authority responsible for transferring control among multiple operators.

The appropriateness of the design of human and automation/robotic integration also depends on how well it fits into the context of use, which may be quite variable. Context of use includes how controllers are trained, the extent and nature of human collaboration around system use, the level of controller fatigue or stress to be supported, and the urgency and dynamics of the tasks being carried out. These factors may interact and conspire such that safety-reduction from one factor increases vulnerabilities from another. All these factors and their interactions can be contributing causes of an inadequate design of HARI.

The effects of an inadequate design of HARI may be immediate and direct, such as an operator selecting an unintended action or a robot harming an astronaut. They may also be long-term and indirect, such as an unusable design contributing to human stress or an unclear design resulting in operation of equipment in configurations that produce unnecessary wear. It is important to be able to measure the consequences of inadequate design much more sensitively than recording the occurrence of rare, extreme accidents. The negative impact of poor design may be measured in terms of task time, workload, use of consumables, occurrence of repairs to actions such as backtracking or redoing, as well as other objective and subjective performance measures. The key point is that poor design can lead to many different types of negative consequences and can be caused by multiple, interacting factors.

Effective risk reduction requires a systems-level analysis of HARI. This is needed to understand and intervene on multiple interacting causes. We also need measures to assess the effectiveness of interventions. The evidence about risk reduction presented in this report is organized around

four types of causal risk factors, selected from the Human Factors Analysis and Classification System (HFACS) categories of error (Shappell,2000). This classification system attempts to identify the point or points in a causal chain of events that produced an accident, typically with behavior identified as an error after the fact. This approach focuses on explaining events after they happen, and providing a causal chain in this explanation. An alternative approach focuses on safety rather than risk reduction and on resilience rather than error (Hollnagel, Woods, & Leveson, 2006; Woods, Dekker, Cook, Johannesen, & Sarter, 2010). In the resilience view an effective design of integration would facilitate effective operation within safety boundaries, while allowing detection of and adaption to changes in safety boundaries possibly due to complex, unexpected dynamics. This newer perspective focuses on system-level and emergent properties, and considers the coupling and integration of distinct factors, such as needs analysis, procedure design, training, operating conditions, and many more. Nevertheless, the summary of evidence is organized here in accord with HFACS contributing factors to risk pertaining to

1) Resource/Acquisition Management including Assignment of Human and Automation Resources,
2) Organizational Climate including perceptions of Equipment, and
3) Technological Environment including
    a) Design for Automation and
    b) Human/Robotic Coordination.

Without proper integration of human, automated and robotic functions, mission goals are at risk.

Levels of Evidence

Evidence presented in this chapter encompasses lessons learned from 50 years of spaceflight experience and ground-based research related to the risk of inadequate human and automation/robotic integration. A variety of evidence types is available, which differ both with respect to the method used to collect evidence and with respect to the context or domain of the evidence. Concerning method, evidence comes from both formal and informal methods. Informal methods include post-hoc reports of naturally occurring events (including incidents and accidents) and case studies. Formal methods include systematic logging or survey of naturally occurring events, and interviews with or surveys of experts. The most formal method of gathering evidence is controlled experimentation. Some evidence is reliant on simulated data from models of human behavior, of automation or robotic system behavior, or of human-system interaction, particularly for circumstances in which it is hard to directly observe and gather empirical data.

A summary of Levels of Evidence may include, but not be limited to:

- Post-hoc reports of naturally occurring events
- Case study

- Expert data
- Expert opinion
- Spaceflight incident data
- Terrestrial data
- Modeling
- Controlled experiments

Concerning context or domain, relevant evidence for HARI may come from space operations (both in-flight and on-the ground), from aviation or other safety-critical work domains, or from other domains with extensive or advanced automation or robotics. Typically, it is difficult to conduct experiments in-flight, so experimental data is most likely to come from simplified tasks or related domains, while in-space data is more likely to come from case studies.

Portions of the evidence consist of summaries of subjective experience data, as well as non-experimental observations or comparative, correlation, and case or case-series studies. It should be noted that some evidence in this report is derived from the Flight Crew Integration (FCI) International Space Station (ISS) Life Sciences Crew Comments Database. Although summaries of ISS crew comments are presented as evidence, the raw comments in the Life Sciences Crew Comments Database is are protected and not publicly available, due to the sensitive nature of the raw crew data it contains.

Evidence

There is extensive evidence that poor integration design produces safety-critical errors. Some evidence comes from in-space applications. There is also a large body of evidence from analog domains, such as aviation and medicine, in which highly skilled users interact with complex technical systems. Evidence and information from analog *mishaps* is used to develop systems involving similar situations and skills. However, this reactive design stance primarily "chases old problems" rather than forestalling the new. A proactive design stance is particularly valuable because, unlike aviation, the experience-base in space is relatively small and circumstances of operations change from mission to mission. Thus, information from prior mishaps is only a partial guide to the many novel situations where we lack specific experience. Future research on HARI will need to investigate those circumstances where we lack direct knowledge. Research will also need to develop methods for extrapolating knowledge from known to less-understood conditions and to integrate the extensive but sometimes fragmentary knowledge we have.

Resource/Acquisition Management

This section considers the ways in which high-level analyses and decisions influence the effectiveness of design, and the evidence that these influences have consequences for safety and efficiency. The better the methods for generating and testing design of HARI, the better the

resulting systems are likely to be. A key research need is the development of effective methods and tools that support generation and testing of HARI design. Research on how such methods can be effectively adopted in practice would also be valuable.

The particular Contributing Factor in focus concerns allocation of functions among humans and automation. This requires identification of the scope of work to be supported and the functions within that work. If there is not an adequate identification of the work functions needed, no partitioning of functions can be very satisfactory. Thus, effective allocation of function depends on effective processes for needs analysis. The factors contributing risk are intertwined.

Serious accidents involving automation in complex operations typically have multiple causes. An initial problem event may be caused by poor integration design, and the response to such an event may be exacerbated by poor integration in some other aspect of the system. For example, the challenge of managing an equipment failure can be compounded if information about system state is provided in a form inconsistent with how people need to use that information (e.g. difficulty in early diagnosis in Apollo 13, (Murray & Cox, 1990), cited in (Woods et al., 2010)). Effective HARI affords multiple opportunities to detect and respond to risky situations. Good design of HARI must also support effectively carrying out the system functions. There are multiple possible conflicting goals in the design and operation of a complex system, for example, between safety and immediate productivity. Assessing trading-offs among competing goals is typical in complex work, which includes known and unanticipated risks. Good design of HARI should support people in effectively gathering and evaluating information to make appropriate decisions about goal tradeoffs, in off-nominal as well as nominal conditions.

An effective process for interaction design requires sound analysis of the work to be supported, or *needs analysis*. This requires an understanding of mission operations, the particular functions that an automation/robotic system is supporting, and of how these functions coordinate with related functions. There are multiple methods for doing this. We use the broad term "needs analysis" to include a variety of analysis methods, including task analysis (Kirwan & Ainsworth, 1992), Work Domain Analysis (Vicente, 1999), and Contextual Inquiry (Beyer & Holtzblatt, 1997). Designing a useful system requires identification of the functionality that should be supported by the system. Kieras, (1996) suggests the primary obstacle in automation design is not writing code, but understanding the problem. This requires a strong understanding of required tasks and how the task functions should be allocated. This task and domain knowledge is essential for most current cognitive engineering analyses. Sherry and Ward (1995) found that the majority of aviation software code was dedicated to understanding and executing the correct automation situations and behaviors, which requires domain expertise. Once the functions are identified, sound design requires further analysis of what functions should be carried out by which agents (human or automation) in what circumstances, i.e., function allocation. Effective

automation design needs to be integrated with process or workflow design (Beyer & Holtzblatt, 1997; Woods et al., 2010).

Once an appropriate needs analysis has been conducted, this information needs to be effectively linked to the design, development, and evaluation processes, which are typically handled as part of software engineering or systems engineering. An explicit needs analysis should guide the requirements specification for an automation or software system. The needs analysis should be used to guide not only verification (that the implemented system matches requirements) but also validation (that the system serves the intended needs). The assurance that a system meets the intended needs is particularly important for safety-critical systems.

A variety of methods exist for testing existing or prototyped HARI designs. Direct assessment by observing people using the system can be very valuable. However this may be impractical or excessively expensive for some complex, safety critical systems. Modeling provides a complementary assessment approach. Operations can be modeled both at the level of a task analysis and at the level of human performance. Systems can be formally checked for specified properties, such as occurrence of a particular unsafe state (Clarke & Wing, 1996). Various modeling methods from cognitive science can simulate human performance (Card, Moran, & Newell, 1983; Gray, 2008; B. E. John, Prevas, Salvucci, & Koedinger, 2004). Modeling is primarily applicable for an existing design, as evaluation, and few models provide direct design guidance. However, modeling a system as it is being developed has provided formative feedback used by designers that substantially contributes to the effectiveness of the final design (Gray, B. John, & Atwood, 1993).

While the importance of needs analysis is widely recognized, at least in the research community, it is often done poorly or not at all. Methods maybe expensive, require subject matter experts, require coordination among stakeholders, or prove otherwise burdensome. The product of needs analysis may not be framed in a way that can easily guide the generation and testing of designs. Similarly, evaluation tools exist but often requirements for expertise and time may limit their adoption. Evaluations may not provide outputs in a form useful to consumers of results. We need research on development and adoption of methods. Lack of practical and effective methods to support consistent generation and testing of good HARI design makes it difficult to consistently produce good designs. Thus lack of good methods is the fundamental cause of the risks produced by inadequate design of human-automation and human-robotic interaction.

Future space operations provide particularly challenging circumstances for designing appropriate HARI: 1) Good HARI design is particularly difficult for new or emerging technologies, which are common in space exploration; 2) Bad outcomes result when risks from many sources combine. A design threat for which operators might successfully compensate in familiar

conditions may show through in novel, risky conditions where integration is most critical to safety and efficiency; 3) Software in space typically lags state-of-the-art, due to environmental testing requirements. This makes it difficult to use what is known about effective designs and design process.

We provide two broad illustrations of the magnitude of risks incurred by inadequate HARI before turning to more specific topics.

Examples

The Mir-Progress collision is an example of a poorly designed operations concept and insufficient needs analysis resulting in a near-catastrophe. The Russian spacecraft Progress 234 collided with the Mir space station, causing the pressure hull to rupture, and nearly causing the Mir to be abandoned (Ellis, 2000; Shayler, 2000). The original operations concept was that Progress would dock automatically with the Mir. Crew responsibilities were primarily to cancel the approach (if necessary) and limited crew displays were provided. Crewmembers were later tasked to perform the docking manually, following a decision not to install automatic docking systems for each Progress spacecraft. This decision was not based on an adequate assessment of integrated human-system performance. It neglected consideration of the types of information crewmembers would need to remotely control another vehicle. Moreover, the crew had no direct visual access to the approaching spacecraft from the command post, nor was range-rate information directly available. Further, the crew was stressed from overly demanding workload and repeated system failures that demanded their attention and contributed to reduced vigilance. The crew last received formal training four months before the docking incident. Multiple causal factors contributed to this event (Ellis, 2000). Moving from retrospective to prospective analysis, ensuring a good match between the needed functionality and the functionality supported by automation is critical to successful operation.

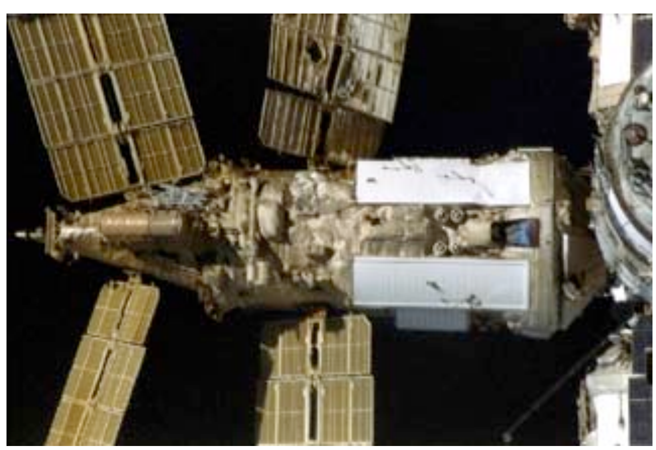

Figure 1. ***Spektr module showing the damaged radiator and solar array on Mir (NASA photograph).***

There is a history of human-automation interaction difficulties for commercial aviation attributable to inappropriate designs. The U.S. Federal Aviation Administration (FAA) and the European Joint Aviation Authority recognized an increase in accidents attributable to problematic interaction between flight crews and flight deck automation. The FAA released a report listing design deficiencies contributing to aviation incidents and accidents and made recommendations for improvement, including the need for new design and evaluation tools in 1996 (*The Interface between Flight crews and Modern Flight Deck Systems*, 1996). Research from the design (C. E. Billings, 1997; Curtis, 1981; Leveson, 1995), the accident investigation (Mellor, 1994; Sarsfield, Stanley, Lebow, Ettedgui, & Henning, 2000), and the regulatory (BASI (Australian Bureau of Air Safety Investigation), 1999; *The Interface between Flight crews and Modern Flight Deck Systems*, 1996) are important. These communities have also illustrated the need to develop methods, tools, and techniques to identify and address human-automation interaction vulnerabilities as early as possible in the design process. Mishaps due to design errors (i.e., mishaps where automated systems performed as designed but aspects of the design contributed to the accident) are increasing (Sarsfield et al., 2000). Although aircraft designs continue to improve and overall levels of safety are increasing, the proportion of mishaps attributable to design flaws is increasing relative to those due to other factors.

Contributing Factor 1: Assignment of Human and Automation Resources
Poor distribution of functions among humans and their tools results in inefficient and unsafe operations, threatening mission completion. It is important to determine which functions should be allocated to the machine and which to the human. Automation design decisions have traditionally focused on optimizing the capabilities of the technology rather than those of the combined human-machine system. Relegating the human to the role of system monitor is often ill-suited. Removing human operators from the control loop can lead to vigilance decrements, loss of operator situation awareness, poor feedback, and manual skill decay.

Several researchers have developed taxonomies of levels of automation (LOA) (Table 8.1, Sheridan & Verplank, 1978; Sheridan & Parasuraman, 2005). Endsley & Kaber (1999) developed a LOA taxonomy that breaks automation into 10 different levels, and can be applied to functions of specific tasks within a system. A task includes four functions: monitoring, generating, selecting, and implementing. The roles of these four functions are allocated to either the human or the computer, depending on the level of automation. Endsley and Kaber (1999) report a complex pattern of effects from a study using a simple analog of package processing work. They found that during normal operation, LOAs that combine human generation of options with computer implementation of a selected option produced superior overall performance. Specifically, this performance was better than the alternatives where only human implementation of options or only computer generation of options was allowed. Automation did not help decision-making, either. However, when automation failed, the relation of performance to automation level was different, and complex. This suggests that ideal allocation may be very

sensitive to the particular capabilities of the operators and the automation, and to the context of operation.

Recent work focuses on how functions should be distributed and shared, using a framework based on collaboration or teaming. The Human-Automation Collaboration Taxonomy (HACT) is a recent framework for design and analysis of collaborative human-automation decision-making (Cummings & Bruni, 2009). The framework identifies three roles, of moderator, generator, and decider, which may be distributed between human and automation for any task. In an experiment using a mission planning task done by experts, performance was worst when the automation was the lead in generating proposals; performance was better when generation was lead by the operator or when operator and system shared responsibility. These findings, in conjunction with those of Endsley and Kaber, suggest that building automation that is "as good as humans" at generating possibilities may be particularly difficult. Another successful planning system allowed the system to first generate a candidate plan, which could then be edited by the human, though this project did not compare alternative automation control structures (Butler et al., 2007).

Additional research is needed to provide the empirical base from which generalizations can be made. A vital but little explored area is distribution of functions across teams of people and system of automation, and the ways in which dynamic allocation is or is not effective. A particularly challenging issue is developing the theoretical framework to guide how findings from one situation can be generalized to another. In turn, such a framework could guide development of modeling tools for predicting effective function distribution early in design and before empirical evaluation is feasible. Tools and methods are needed for function allocation, as with the identification of needs and functions to be allocated.

Organizational Climate

Organizational climate is an important contributor to safety. One aspect of this is how humans perceive the automation with which they interact. The way operators view an automated system has a strong influence on how effectively the human-automation system functions. In this context, researchers have focused on the degree of trust and reliance that humans place on their automation.

Contributing Factor 2: Perceptions of Equipment

In a particular setting, an operator may have too much or too little "trust" in the system, and these situations may result in over- or under-reliance on automation, respectively. An example of over-reliance on automation, with serious outcomes, involved failure to detect that the global positioning system (GPS) component of the auto-navigation system on a cruise ship had failed. As a result, the Royal Majesty was run aground (Degani, 2004; Lee & See, 2004). Operators were complacent and did not effectively monitor whether the system was behaving as designed.

When trust is high, operators are likely to rely on automation, i.e., to act as indicated by alarms or hazard indicators, but may be too "compliant" and fail to respond to unidentified hazards or hazards incorrectly identified by the system (Sheridan & Parasuraman, 2005).

When accidents do occur, their significance should be understood in terms of the policy of the operator, or operator calibration. The operator policy means the way the operator, in general, uses the automation. This might include how much time the operator spends monitoring the automation, or how often the operator does what is recommended by the automation. The optimal policy is not necessarily one in which the operator monitors or complies with the automation all the time: the operator may have other things that make demands on his or her time, and the operator may justifiably believe automation is not always to be relied upon. Calibration refers to how well the operator's policy of use aligns with automation characteristics. Because any automation is imperfect, any system will produce some distribution of error types; for diagnostic systems this can be characterized as misses and false alarms. Assessing the accuracy of operator calibration, not the occurrence of an individual accident is important for understanding the design quality of HARI. Frequently, operator calibration is good (Lee & Seppelt, 2009) and air traffic control (ATC) is one domain where this has been extensively studied. Operator reliance on automation is sometimes affected by workload (Kirlik, 1993; Wickens & Dixon, 2007), and by sudden change in automation performance, as well as by superficial aspects of an interface (Lee & Seppelt, 2009). Additional issues may arise at the transition point between prior, manual control of a function to new, automated control, as this change typically requires a reorganization of the operator's tasks (Sarter, Woods, C. Billings, & Salvendy, 1997).

In general, it is challenging to determine the contextually appropriate, rather than designer-intended, use of automation. It may, however, be feasible to do this for diagnostic and warning systems, where most research on operator perception of automation has focused. Here, at least in principle, there is accuracy data that an operator might use for calibrating reliance. Even here, it is a challenge to measure accuracy of the automation and what the appropriate response to warnings should be. Effective integration might be viewed as the automation providing information to enable anticipatory action, rather than as alerts to impending collisions (Wickens et al., 2009). Few studies have looked at overall effectiveness of using automation or of operators' choices for when to engage an automatic aid at all. In one study that did pursue this, Kirlik (1993) sought to explain why operators did not use an experimental autopilot to off-load tasks at peak work periods. Modeling of task demands suggested that operators' strategies (including nonuse) were more optimal than that intended by the designer.

Adaptive automation is a next step to managing change in authority and in determining what information is provided to the user. While this may be able to strategically aid operators, e.g.

when suddenly stressed by high workload, this can also reduce transparency, making it difficult for the human to determine the state of the automation or of the system controlled.

Risk arises from poor HARI when the way operators use automation is not well aligned with the automation's capabilities. This frequently has fallen outside the focus of automation design, since the intent is typically to build automation with high benefits (e.g. accuracy) and low costs (e.g. set up). Thus, design to support users in determining how, in context, the system is most effectively used is not often addressed. Policies stipulating use may be effective for routine procedures, but may be inadequate for unusual situations. Additional research is needed to understand both what determines the most effective use of a system in context and to understand how people decide how to use the system.

Technological Environment

Interaction with the engineered environment is central to human-systems integration. Both automation and robotics concern computer-mediated systems that typically act on the physical world. Integration or coordination with humans is a central concern for both. Nevertheless, a somewhat distinct set of issues and research has developed around each. Once the decision to include automation or robotics in a socio-technical environment is made, the design of its integration with humans strongly impacts performance

Contributing Factor 3: Design for Automation

This section reviews impacts not already addressed, specifically concerning transparency. Transparency is also closely related to quality of information display and to training, which are each discussed in separate reports. Interaction with the automation should be transparent, so that operators can easily tell the state and capabilities of the system. Lack of transparency may produce: 1) inability to determine the current state of the automation or of the system it is controlling, and 2) lack of understanding of what the automation can do. In turn, this leaves the user unprepared to diagnose or intervene in the automation behavior.

Designing for transparency is very difficult for systems that are very complex and require many displays and controls. Kieras (1996) points out two strategies used for handling complexity: distributing displays and controls across physical space, as on older "switch and meter" systems, and distributing displays and controls across time, as with newer software-based systems, using multiple modes.

In older electro-mechanical systems, displays and controls were fixed physical devices, and instrumentation was spread over the surfaces needed to contain it. In these systems, inadequate design led to errors because information was often widely and awkwardly distributed. A critical factor in the Three Mile Island events was display layout: a distributed and awkward

arrangement made the state of the system hard to grasp, and so failure diagnosis was difficult (Leveson, 1995).

In software-supported control, the display and control space is usually very limited. In many modern applications, displays and controls are restricted to a computer screen (sometimes very small) with mouse and keyboard. Rather than spreading information across space, information is spread across time with different information displayed in the same space at different times. A system *mode* is a structured collection of interaction options usually used together. One mode is selected from a set of modes, depending on context. Modes are used with electro-mechanical systems as well as "glass cockpit" and other software-controlled systems, but mode complexity increases with software-controlled systems.

Mode related errors are known contributors in aviation accidents and incidents. Lack of transparency often results from issues related to modes. There are two types of problems: difficulty in telling what mode a system is in and difficulty telling what a mode will do. For example, pilot training may only teach selective modes, leaving out unusual modes or those not used in airline operations policy. Pilot performance has latent problems, revealed in non-normal situations (Sarter & Woods, 1994). Problems can result because the system was in a mode not expected or identified by the pilot, the pilot could not predict behavior in that mode, or both (Sarter et al., 1997). In 1994, an A300 airplane crashed at Nagoya Airport. Prior to the crash, the mode had been inadvertently changed to "Go Around" rather than land. The pilot fought against the autopilot and was unable to gain control. Lack of awareness that the mode had been changed, and inability to predict how automation and human control would affect behavior in these conditions were both likely contributors (Sogame & Ladkin, 1996).

On Apollo 10, at the end of the second pass over lunar landing site 2, the two crewmembers were preparing to separate the two stages of the lunar lander and return to the command module in orbit around the moon when the mode of the guidance and navigation system was inadvertently changed by one of the crewmembers. A couple of seconds later, the other crewmembers reached up, without looking, and changed the mode of the guidance system, which canceled the change that had been made by the first crewmembers. As a result, the lunar module, *Snoopy*, began firing thrusters in all axes, pushing the gyroscopes into gimbal lock and making the navigation system useless until it was reset. The crewmembers then toggled the navigation system switch again and, although he now put it into the mode it should have been in to start with, it made things worse. At this point the crew overrode the computer and took manual control. The incident lasted about 15 seconds, during which *Snoopy* made eight complete rolls. It was estimated that if the crewmembers had not regained control within another 2 seconds, it would have been too late to avoid impact with the moon. Without clearly communicated information

about actions and state changes of both automation and crew, there is real risk to safety from accidental operations (Shayler, 2000).

An Airbus test flight with very skilled crew also ended in a crash following a combination of conditions that produced both unexpected mode change and inability to compensate for the autopilot behavior in this mode (Aviation Week and Space Technology, 1995); also discussed in (Sarter et al., 1997). This case involved an automation-initiated mode change due to the extreme conditions of the test, and inadequate time to diagnose and recover from the control policy in this mode. Problems were compounded because automatic decluttering, which is designed to simplify the displays in an emergency, removed all flight mode enunciators from the display. This left the pilot with no visible indicator of control mode. In another incident, unexpected effects of disengaging the autopilot led to Pilot Induced Oscillation (PIO), resulting in passenger injury (Encounter with Wake Turbulence, Air Canada, Airbus A319-114 C-GBHZ, 2008); lack of understanding the effects of mode change was a probable contributor.

Implicating mode issues in accidents illustrates their criticality, but accident analysis does not provide a method of systematic and controlled investigation of phenomena. Several laboratory experiments have investigated the extent and nature of mode errors. Sarter and Woods (2000) constructed challenging scenarios to be flown in high fidelity simulators. The realistic but challenging scenarios required 18 First Officers to respond to unusual conditions, including unusual automatically triggered mode transitions and unusual clearance instructions. Across 5 unusual probe events requiring pilot action, only 39% of responses were accurate and timely while for 34%, appropriate action was never taken (Table 2, Sarter & Woods, 2000). This study shows that even with modern designs and expert users, mode issues can have a serious impact on performance, particularly when operating in challenging conditions.

Risks from poor transparency concerning mode state and mode behaviors are most often triggered by some unfamiliar combination of conditions, frequently including operation in a less safe environment. This may result in mode changes triggered by the automation or by a partner, as well as by a key operator. An operator, such as the Pilot Flying, may then be unaware of the current mode and be in a mode whose behavior is less familiar, while also operating in dangerous external conditions. While the conditions that trigger problems may be rare in aviation, unfamiliar mode combinations and unsafe environments will occur more frequently in space. Complex automation is powerful in part because it provides multiple control policies, which can be selected based on circumstances. Yet managing different modes is a key locus of ineffective integration. Understanding design and design trade-offs in managing complex control policies is a critical area of research. Methods and tools to increase efficiency of research and for generalizing findings are also needed.

Contributing Factor 4: Human/Robotic Coordination

Coordinating human and robotic activities for future space exploration creates challenges in many areas, but particularly for Human-Robot Interaction (HRI). Most research in this field is in its infancy, as evidenced primarily by the fact that human teleoperation, supervisory control and teaming have not yet been widely implemented in space, military, industry and the like. Current in-space applications are limited to the Shuttle and Station robotic arms, and an experimental flight of the AERCam Sprint robot in 1997 (Pederson, et al, 2003), all of which are controlled by on-orbit crew via direct teleoperation. Surface exploration robots such as Sojourner, Phoenix and the Mars Exploration Rovers (MERs) have been used extensively for over a decade but their operations are open-loop, where the human must send sequences of commands rather than act on fed-back information in real-time due to the long signal time delays between Earth and Mars. We will be facing increasing complexity of future robotic systems as we move from direct teleoperation to supervised teleoperation and autonomous control, with both spatial and temporal distances between operator and robotic agent. Employing human robot teams will require a level of coordination not previously realized between teams of robotic controllers, astronauts and mission controllers. Without overcoming the complex and varied HRI challenges facing the system designers, we are at risk of not fulfilling the roles envisioned of NASA human robot systems.

Risk is inherent due to our lack of knowledge and experience with how best to design HRIs to meet the capabilities required of future human-robotic (HR) systems. However, there have been many lessons learned from the years of Shuttle, Station and Mars robotic operations. McCurdy (2009) describes the iterative process that evolved the tools used by the Mars robot operators to plan and execute commands. After tactical processes were implemented, they found that they were not able to support the deadlines that the tasks demanded. Planning tools were developed to meet the necessary timelines, but these too suffered inefficiencies (Norris, et al., 2005). After applying human-centered principles, several interface issues were identified. There were large numbers of tools designed by different groups for differing purposes, that were inconsistent and non-cohesive, which led to steep learning curves as well as performance issues. Their primary timeline tool was based on outdated legacy software and developed with a different user population in mind; this led to significant effects on their ability to make or miss an uplink deadline. Modifications were made to this tool for the Phoenix Mars Lander mission.

Optimized robotics operations are critical for the successful execution of extravehicular activities (EVA) onboard the ISS. According to data contained in the FCI ISS Life Sciences Crew Comments Database, this includes the proper set up and configuration of the onboard Robotic Workstation (RWS) and subsequent actuation and execution of arm operations. The RWS for both the Space Shuttle Remote Manipulator System (SRMS) and Space Station Remote

Manipulator System (SSRMS) consists of a laptop computer, translational and rotational hand controllers, three video monitors and a display and control panel. Robotics workstations onboard the ISS are currently located in the US Lab, Cupola and Japanese Pressurized Module (JPM). Although the workstation can be operated by a single crewmember, in practice, crewmembers prefer that RWS activities be conducted with two crewmembers.   One person acts as the primary controller, and the second crewmember is dedicated to managing camera operations, observing procedures, and confirming the direction of motion. They report that this allows them to increase their situation awareness and maintain a system of checks and balances. They have noted that the second crewmember does not necessarily have to be another on-orbit crewmember and could alternatively be a ground crew operator, however this depends on maintaining real-time communication with Mission Control, which is not always possible. The crew have cited improvements that are needed to the HRI controls, including more camera views and assistive overlays.

Figure 2. ***European Space Agency astronaut Leopold Eyharts, STS-123 mission specialist, and astronaut Greg Johnson, pilot, perform work at the robotics work station in the U.S. laboratory, Destiny.***

Figure 3. ***Completing an EVA activity using the robot arm with a crewmember on the end from inside the shuttle requires careful allocation of functions and task planning.***

Given the already strained robotics crew resources and the large number of robotic and EVA operations expected for ISS, ground control is an attractive method for off-loading on-orbit crew time and maximizing the efficiency of end-to-end ISS operations (Coleshill, et al., 2009). In 2005 during STS-122/ISS 10A, the planned efficiencies were finally realized as a majority of pre and post operation configurations for SSRMS were allocated to ground control. Adjustments had to be made to reduce the constraints on the step size of arm motions allowing greater movement distances in less time. These were originally implemented by safety to reduce the duration of each maneuver, thereby limiting the number of unplanned loss of communication signals between the ground and the ISS. Task analysis was able to determine the best allocation of operations between the on-orbit crew and the ground. This type of coordination will be critical as control of remotely located robotic agents becomes more commonplace in an environment of increasing time delay and loss of signal (LOS) events (Aziz, et al., 2010).

For Shuttle and ISS operations and in cases where the time delay allows, ground control should be used to the greatest extent possible to reduce EVA time and accomplishment risk. For surface operations, this could involve a robotic operator in a habitat controlling an external robot to maximize the efficiency of surface EVAs. Currently, some barriers to extensive ground control exist because mission controllers place a high level of restriction upon the type and methods of operation allowed until more experience is gained. Additionally, the robotic systems along with their human interfaces were designed for on-orbit use and are not tailored to the needs and limitations of a remote operator. At present, the range of operations is limited and while crew on-orbit time has been relieved, the overall timelines have not been reduced (Webb, et al., 2009).

The Special Purpose Dexterous Manipulator (SPDM), or Dextre is a two-armed manipulator mounted on the SSRMS as part of the Mobile Servicing System. It is designed to perform dexterous robotic maintenance, payload servicing, and other miscellaneous tasks. Even before the system was launched in 2008, it was determined that within the accepted operations constraints, the timelines associated with its use would be excessive and beyond the crew resources that were available. A Technical Interchange Meeting was convened in 2002 to look at the prohibitively long end-to-end timelines. They are due in part to robot design, wherein one arm is required for stabilization, resulting in tasks being reduced to single-arm tasks. There is also no direct operator viewing, large numbers of procedural steps, and robotic tool manipulation is required for almost all Removal and Replacement (R&R) situations (Caron, 2004). Additionally, procedures are entirely pre-planned and approved, leaving little to no ability to respond to real-time anomalies or contingencies. This plagued a recent SPDM activity wherein operations had to be halted for over a day while they re-planned based on an anomaly. Several enhancements such as auto-sequencing and targeting overlays are in the early stages of development to help mitigate these issues.

Figure 4. In June 2008, Dextre was moved atop the Destiny Laboratory Module of the International Space Station (ISS), completing tasks prior to the the STS-124 mission's deployment of Japan's Kibo pressurized science laboratory.

Currie and Rochlis (2004) conducted a study using the SPDM trainer to assess the feasibility of ground control operations under a time delay, a condition that will become of primary concern for robotic operation as we move beyond Low Earth Orbit exploration. Astronaut test subjects conducted an Orbital Replacement Unit (ORU) R&R activity with simulated six and eight second telemetry and video time delays (LOS conditions were not modeled in this experiment). Crew found that they could easily adapt to the delays and all subjects were able to successfully complete the activity. Interestingly, more than fifty percent of the ground control operational time was spent not on motion command inputs via the hand controllers, but on manipulating displays, cameras, and controls to gain and maintain situation awareness. This implies that performance increases are to be gained from more effective interface designs (Carrie & Rochlis, 2004).

Human interface improvements such as augmented reality have also been investigated (Maida, et al., 2007). Although a human-in-the-loop command mode is available for SPDM, it is operated almost exclusively using automated sequencing from the ground, where camera views and situation awareness information is at a minimum. Their results indicate that overlays improve performance in maneuvering an ORU in preparation for inserting it into a receptacle, and three performance metrics showed statistically significant improvements in prepositioning accuracy using overlays.

While robotics operations conducted onboard the Space Shuttle and ISS involve minimal autonomy with ground crews supporting and monitoring all aspects of crew robotics tasks, future spaceflight missions will involve increased autonomy and potentially decreased ground support during robotics operations. Kadous, Ka-Man Sheh & Sammut (2006) highlight that teleoperation

is a vital consideration for robotics activities and interaction with robots. Successful robotic operations rely on optimized design of user interfaces. This includes the development of user interfaces that allow for varying levels of autonomy, cooperation and interaction between humans and robots (Kadius, et al., 2006).

The art of assessing human-robotic interfaces and the methods and metrics used to do so are still emerging. While specific, agreed upon attributes for human-robotic user interfaces do not necessarily exist as of yet, Kadous, Ka-Man Sheh & Sammut (2006) highlight several guidelines to consider. These guidelines are derived from previous design principles developed by Scholtz (2004). They include awareness, efficiency, familiarity and responsiveness. Awareness involves the proper presentation of information to ensure operators have a complete mental model regarding the robot's internal and external state. This necessitates creating a balance to avoid overloading the operator with too much information. Efficiency involves requiring as little operator hand and eye movement as possible and ensuring focus of attention. Familiarity involves a focus on the inclusion of intuitive information and concepts that the operator is familiar with and an avoidance of the presentation of unfamiliar information. Finally, responsiveness guarantees an operator is receiving continuous feedback regarding operations.

Keyes et al. (2010) similarly contend that overall awareness is key for the successful completion of robotics tasks. Robotic operations will often occur outside of the human operator's line of sight. This requires the human to have acute knowledge of all aspects of the working conditions and environment that the robot will be operating in as well as the state of the robot (Keyes, et al., 2010). Drury, Keyes, and Yanco (2007) define this level of human-robot awareness by five individual characteristics, namely, human-robot awareness, human-human awareness, robot-human awareness, robot-robot awareness, and the human's overall awareness of the mission (Drury, et al., 2007). Kadous, Ka-Man Sheh & Sammut (2006) contend that robot operations should embody the operator, while the operator in turn should strive to imagine themselves as the robot (creating a sense of 'presence'), or in the same environment as the robot, during operations. However, this methodology can encounter barriers such as the varying morphologies between the robot and the operator, and issues with sensing and perception. Operators may encounter problems with control and interaction if they feel they cannot relate to or sense the robot's operations. Ensuring complete situational awareness is available through the HRI is critical.

Trafton, et al. (2005) also provide guidelines for the design of human-robot interfaces. They suggest a human-to-human interaction model, which involves using interactions between people as a guide to design the planned human-robotic interactions. While there are many aspects of human-to-human interaction, a desired characteristic of human-robotic interaction is a human's ability to apply alternative viewpoints and reason from this perspective, although it may vary from their day-to- day point of view. Various forms of perspective taking can apply to a

multitude of tasks and situations. Although this seems to likely be a successful guideline for human-robot interface design, recent literature and research rarely address perspective taking and robots.

Trafton, et al. (2005) conducted research to attempt to understand how perspective taking is already used or could be applied to spaceflight EVA. They observed and analyzed EVA training activities at the NASA Johnson Space Center Neutral Buoyancy Laboratory (NBL) and determined that spatial-perspective taking was occurring during these activities. This involves such examples as the meaning of the word "down" having a totally different definition in a six degree-of-freedom EVA environment (where one would have to know what "down" was in relation to) as opposed to on the ground. This weightless operational environment can create specific challenges from a spatial perspective. Based on this applied analysis, three guidelines were developed to assist with understanding and designing human-robotic interactions from a human-human interaction point of view. They include: 1) ensuring that all aspects of robotic representation and cognitive-like functioning (such as reasoning and perception) are as human-like as possible, 2) building cognitive systems for the interactions based on integrated cognitive architectures, and 3) applying heuristics and principles for collaborative activities that align with human expectations. Overall, similar to human-to-human perspective taking, a robot should be able to assume and adapt to multiple perspectives while performing tasks to allow for optimized human-robotic interaction. Lastly, the researchers discuss how the issue of collaboration between humans and robots is one of the most difficult aspects to study. Their analysis attempts to answer questions such as when to collaborate, when to ask for help, and how to respond to assistance.

McIntyre, et al. (2003) have focused their research on the nature of teams, their interrelations, and how they develop team cohesion. While this research is in reference to human teams, these concepts can apply to interactions within human-robotic teams. Team cohesion can be defined by both social and task cohesion. Social cohesion involves the desire to achieve team affiliation. Task cohesion involves the efforts of the team to achieve tasks and goals together as a team (Craig & Kelly, 1999). McIntyre, et al. (2003) highlight a teamwork process model known as the "Dickinson-McIntyre model" (Tedrow 2001) which can be mapped to the development of human-robotic teams. The model details seven components of teamwork which provide a framework that leads to optimized task performance. The elements include communication, team orientation, team leadership, monitoring, feedback, backup behavior, and coordination (Tedrow, 2001).

Ferketic et al. (2006) address NASA's "Vision for Space Exploration" (VSE) initiative established in 2004 and its primary goal of establishing a human-robotic program for future exploration. Unlike previous exploration programs, VSE places specific attention on human-

robotic interaction capabilities and on integration to enhance exploration, safety and mission success. This is significantly important and complex given potential long duration and deep space missions that will involve increased crew autonomy, limited communication and minimized dependence on ground support. Increased reliance on human-robotic interaction built into future mission objectives will lead to a significant change in the philosophy for the design and execution of missions. Crews will be expected to be comfortable and familiar with robotic user interfaces, and these interfaces must optimally support mission objectives (Ferketic, et al., 2006).

Similar to many other researchers, Ferketic et al. (2006) highlight the current lack and increasing need for establishing standards to define effective human-robotic interaction and design interfaces. While human engineering and human-centered design standards can apply, specific guidelines are needed based on the unique demands of long-duration spaceflight missions and the nature of interactions and objectives related to human-robotic operations. Developing HRI standards can be extremely complex as most robots are developed with customized interfaces and methods of interaction, and the level of coordination and control required is often highly task dependent. In order to standardize these types of operations and interactions, common metrics and measures must be developed. This includes fundamental commands, operations, and interfaces that lead to expected and similar responses from the robots. This will subsequently lead to increased consistency in robotic actions, operators' familiarization and comfort with control and operation of the robots, and decreased risk of errors and mission objective failures. In an effort to properly develop standards for human-robotic interactions in spaceflight missions, Ferketic et al. (2006) identify their own essential guidelines. These include:

- define the capabilities and limitations of humans and robots
- develop user interfaces which are suited to the task at hand
- address any related challenges to efficiency and operations to allow for human-robotic collaboration
- establish superior prototyping and evaluation methods

These guidelines will allow for the evolution of human-robotic interaction, increased safety, and successful, collaborative task completion.

Risk in Context of Exploration Mission Operational Scenarios

Future exploration-mission scenarios will increase in duration and in distance from earth. This will require developing new technology, new work methods, and new ways of ensuring that these novel elements are suitably integrated. In particular, new automation and robotic technology and new ways of using technology to accomplish mission objects are needed. Missions carried out in space will need greater flexibility and less dependence on ground support, and new interaction between ground-based resources and crew will also be needed.

Risks from inadequate design of human-technology interaction will increase as mission requirements become more demanding and as missions are carried out in unfamiliar circumstances substantially different from our experience base. Human factors principles will need to be extended and applied to reduce risk.

Space operations are tightly coupled, and probably will trend more so. That is, one event or aspect of the system can affect many others, often quickly or with limited ability to intervene effectively. This means that problems may compound and propagate extensively and rapidly. For example, a poorly controlled robot might damage a craft or habitat; damage that might be inconsequential on earth could lead to a cascade of threats. Conversely, benefits from good design may propagate. If HARI supporting routine tasks is well-designed, it means tasks can be done more quickly and with less crew fatigue; in turn, this leaves the crew with more resources to be better prepared to deal with safety-critical events.

Good design is foundational to reducing integration risks, both of safety and of failure to complete missions due to inefficiency or ineffectiveness. While poor integration design may be compensated by extensive training or other work-arounds, good design reduces costs, increases efficiency, and enhances safety. Most space exploration missions are carried out through human use of technology (automation/robotics). Thus, the scope of impact of the design of human-automation/robotic integration is very large. In turn, applying effective design methods and implementing effective designs can have a very large, beneficial impact on operational success. Gaining the benefits of good design also requires effective implementation and evaluation.

Conclusion

The success of future exploration missions depends, even more than today, on effective integration of humans and technology (automation and robotics). This will not emerge by chance, but by design. Both crew and ground personnel will need to do more demanding tasks in more difficult conditions, amplifying the costs of poor design and the benefits of good design. This report has looked at the importance of good design and the risks from poor design from several perspectives:

1) If the relevant functions needed for a mission are not identified, then designs of technology and its use by humans are unlikely to be effective: critical functions will be missing and irrelevant functions will mislead or drain attention.
2) If functions are not distributed effectively among the (multiple) participating humans and automation/robotic systems, later design choices can do little to repair this: additional unnecessary coordination work may be introduced, workload may be redistributed to create problems, limited human attentional resources may be wasted, and the capabilities of both humans and technology underused.

3) If the design does not promote accurate understanding of the capabilities of the technology, the operators will not use the technology effectively: the system may be switched off in conditions where it would be effective, or used for tasks or in contexts where its effectiveness may be very limited.
4) If an ineffective interaction design is implemented and put into use, a wide range of problems can ensue. Many involve *lack of transparency* into the system: operators may be unable or find it very difficult to determine a) the current state and changes of state of the automation or robot, b) the current state and changes in state of the system being controlled or acted on, and c) what actions by human or by system had what effects.
5) If the human interfaces for operation and control of robotic agents are not designed to accommodate the unique points of view and operating environments of both the human and the robotic agent, then effective human-robot coordination cannot be achieved.

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List of Abbreviations

ATC	Air Traffic Control
EVA	Extravehicular Activities
FAA	Federal Aviation Administration
FCI	Flight Crew Integration
GPS	Global Positioning System
HACT	Human-Automation Collaboration Taxonomy
HARI	Human Automation/Robotic Interaction
HR	Human Robotic
HRI	Human Robot Interaction
ISS	International Space Station
JPM	Japanese Pressurized Module
LOA	Levels of Automation
LOS	Loss of Signal
MERs	Mars Exploration Rovers

NASA	National Aeronautics and Space Administration
NBL	Neutral Buoyancy Laboratory
NEO	Near-Earth-Object
ORU	Orbital Replacement Unit
R&R	Removal and Replacement
RWS	Robotic Workstation
SPDM	Special Purpose Dextrous Manipulator
SRMS	Space Shuttle Remote Manipulator System
SSRMS	Space Station Remote Manipulator System
VSE	Vision for Space Exploration